Electrical Power and Energy Systems 105 (2019) 642–659

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Model based approach for planning dynamic integration of renewable energy in a transitioning electricity system

Tarun Sharma*, P. Balachandra

Department of Management Studies, Indian Institute of Science, Bangalore 560012, India

ARTICLE INFO

Keywords:
Electricity system transition
Generation expansion planning
Renewable energy integration
Power system modelling
Sustainability transition

ABSTRACT

Reality of climate change threats have spurred mitigation interventions across the world. For electricity sector, the interventions are predominantly in terms of mainstreaming renewable energy sources. Consequently, there is a consistent increase in the share of renewable energy-based electricity systems which has caused emergence of several new challenges. The challenges have emerged both with respect to planning and management of the transitioning electricity systems. These new challenges are because of shift away from supply-chain influenced conventional energy resource supply to nature influenced dynamic renewable energy resource supply; shift from conventional firm power to renewable intermittent power; operational complexities due to frequent and steeper ramps; and need for matching dynamic demand for power. We propose, develop and validate a novel approach for better representation of these resource-supply-demand dynamics in evolving suite of generation expansion models with operational details. First, we discuss development of an electricity generation expansion planning model with operational details. Second, to model the dynamic nature of renewable energy resources and demand for power, we develop an approach for generating annual wind and solar resource profiles, and representative load curves respectively, and harmonizing them before they are fed into the generation expansion model. We validate this approach using India's electricity system data and use the model to evaluate implications of varying levels of renewable energy integration. We find that this increased penetration of renewable energy while bringing significant climate change benefits creates substantial capacity redundancy leading to lower capacity utilization of the overall system.

1. Introduction

Electricity is current of electrons maintained through a motive force extracted from energy gradients, i.e., wind, solar, hydro, combustion. And the electricity system operates by real time matching of demand and supply. On account of increasing demand and the retirement of existing capacity, decisions are made about deployment of new power generation capacities. These decisions involve selection of energy technologies from an entire gamut of different options. With advancements in science and technology, there are several technological options for supplying electricity to meet demand with either more efficient use of conventional fossil fuels or without using them at all [1–3]. Each power generation technology is characterized by a set of attributes and attribute values determine how generation technology contributes to or impacts technical, economic, social and environmental goals of electricity system, i.e., load (or demand), reserve margin and system externalities, e.g., emissions, water use. Every energy technology has significant benefits as well as costs [4]. Fossil fuel (coal and natural gas) based technologies are cheaper and reliable but emit more CO_2 and pollutants, which has implications for climate change and local pollution. In contrast, renewable energy sources such as solar and wind do not have operational emissions, but they are not always available due to fluctuations in their resource availability, i.e., solar insolation and wind respectively which gives rise to a situation where both demand and supply have prominent variations at short time scales [5]. The major transformation in electricity systems is a shift from resource planning and fuel procurement management influenced fossil fuel supply to renewable resource supply that is influenced by nature. Thus, a loss of human control over resources, i.e., renewable energy adds further challenges as well as complexity to planning this transformation. Consequent upon all these considerations of technical feasibility, reliability, availability of natural resources and emissions, generation technology evolution in the electricity space is a matter of intense scientific enquiry as well as public discourse [3,6–11].

There is an entire array of possible interventions for electricity system in transition which Lund, et al., (2015) in their review classify

* Corresponding author.
E-mail addresses: tarunnitham@daad-alumni.com, patilb@iisc.ac.in (T. Sharma).

https://doi.org/10.1016/j.ijepes.2018.09.007
Received 7 March 2018; Received in revised form 8 August 2018; Accepted 8 September 2018
Available online 11 September 2018

as: interventions on demand-side, network (i.e., transmission and distribution), supply-side (i.e., fossil and renewable), and, the electricity market [12]. They can also be categorized into – (i) time shifting of load and/or generation which helps in better matching of demand and supply: demand side management (responsive loads), coupling with other energy sectors, i.e., transportation, storage, smart grids (prosumers, i.e., electricity consumers who produce their own electricity at different points in time), and (ii) spatial aggregation through transmission network [13]. Out of all these aspects, in this paper we focus on electricity generation portfolio – which is expected to undergo an imminent and massive augmentation – with emphasis on dynamic integration of renewable energy into the expanding electricity generation capacity. Transmission and storage although important are beyond the consideration of this work. This emphasis is in view of the imminent climate change mitigation interventions which intend to move the system away from conventional fossil fuel-based power generation and seek a mainstream role for solar and wind energy dominated renewable energy systems. These in turn are expected to cause emergence of several new challenges as brought out in the subsequent sections.

In the following section we review the state of art identify the relevant open questions and issues, and, focus on contributions of this work relative to them. Underscoring the complexity and imminence of planning in an electricity system with significant renewable energy, which is a shift away from traditional supply-chain management decision making for securing supply of fossil fuels to depending on nature influenced uncertain renewable energy resource supply, this paper contributes to bridging the methodological gap by proposing an approach for better representation of renewable resource dynamics with in the evolving suite of generation expansion models with operational details for planning dynamic integration of renewable energy in transitioning electricity systems. The approach utilizes clustering algorithm on the time series data on electricity demand and resource availability for wind, hydro and solar to generate numeric inputs for the mathematical model.

2. Literature review

The solution to the problem of electricity system generation expansion lies in establishing the relationships amongst the generation options, availability of corresponding energy resources, electricity system feasibility, i.e., real time matching of demand and supply with additional requirement of reserves, financial resource requirements for exercising a particular choice of technological pathway and systemic implications of such a choice. As a first step these relationships must be established after which the problem essentially is to arrive at an optimal combination of technologies, which meet the electricity system feasibility requirements, has relatively higher input efficiency, and produces desirable outcomes in terms of sustainability. While developing roadmaps for 139 countries [14] have called for electrification of all energy sectors which provides context for researching generation expansion. About the first aspect, literature has recent instances of different electricity system network representation/configurations/specifications to account for and model the dynamics introduced by a changing technology landscape, i.e., variable renewable generation in particular [1,13,15–18]. As far as the second aspect is concerned, i.e., arriving at an optimal combination of technologies which meet the system feasibility requirement, generation expansion problem has been formulated with multiple objectives: cost minimization, revenue stream maximization, minimization of cost of non-access, minimization of emissions of CO_2 and N_2O and SO_2 [8,15,19,20].

Generation expansion planning models in literature typically deal with economic and environmental considerations. From a time horizon perspective, power system studies vary from hours to weeks, e.g., unit commitment, to multiple years as is the case with generation expansion models [21,22]. Beyond these conventional categories, Balachandra & Chandru [19] have emphasized on the need for another category of intermediate range tactical planning models by integration of the dynamics of demand variations to introduce the realism of operational planning with the perspective of strategic decision making to minimize cost of electricity supply demand matching. This was one of the earliest suggestions to move away from traditional load duration curve, towards inclusion of operational planning details with in the strategic decision making. More recently Palmintier & Webster [16] have demonstrated the need to include operational details which were conventionally dealt with in unit commitment models in the capacity expansion models to capture the intra hour dynamics introduced by integration of variable renewable electricity, i.e., frequent and bigger ramps, which has been corroborated by several researchers [23,24].

Balachandra [25] has analyzed the implications of private sector participation in capacity additions on public utility and consumers to show negative impacts of high guarantees offered to the private sector in terms of reduced utilization of both the existing and new public capacity and high consumer prices. In present context, similar issues about capacity utilization and consumer price, i.e., renewable integration causing conflict of capacity utilization between renewable capacity and conventional capacity and driving the cost up, are associated with integration of renewable energy [16,26]. It entails high flexibility requirements from conventional generators which has implications for their design to ensure safe operation [27]. These concerns around capturing the operational dynamics of renewable energy are relevant for several nation states where variable renewable electricity generation has been promoted through government initiatives in terms of setting ambitious targets [28] and several policy directives [8] like renewable purchase obligation, renewable energy certificates, and feed in tariffs.

To account for variable renewable electricity generation, which is expected to constitute the evolving generation technology pathway [12,28–30], there is a demonstrated need to include operational level details [19] and inter hour dynamics to capture the generator cycling behavior i.e., startups, minimum output levels in the conventional generation expansion planning models [6,16]. While generation expansion models with operational details have been evolving [16,31–34] degrees of freedom remain as to how electricity system components, i.e., temporal resolution, resource variability, technological operation etc. are represented within these models. There is a tradeoff between the planning time horizons (length) versus the operational details and within year temporal resolution that can be accounted for in a generation expansion model. This pose a significant modelling challenge and is a fertile ground for active research [9,24,35]. Researchers have made efforts to reduce the computational load and overcome intractability by implementing column generation approaches to [36,31] cover the specificity of contemporary efforts to deal with these issues and what they lack. For sake of brevity we don't repeat those findings here. They go on to present a multi-region, multi-period generation expansion model with realistic operational details and use one 24-h load curve for each month for each of 12 months across years with in their model [31,37]. In general, literature points to the lack of a nuanced study of operational regimes, spatial and temporal resolution with in generation expansion modelling in general [2,3,35] and specifically to lack of proper treatment of how temporal resolutions are determined and derivation of corresponding resource availability and demand profiles.

We deal with this issue and present an approach to systematically tackle the questions around how supply and demand are represented in generation expansion models and derivation of representative profiles used to study renewable integration in power systems. This study contributes to the new body of knowledge by underscoring the need for systematic representation of supply and demand variations, and, capacity utilization in generation expansion models which is followed by proposition and implementation of methods for the same which includes obtaining load profiles from aggregate projections and harmonizing the extracted representative loads and resource profiles to ensure

temporal correlations amongst them. Capacity utilization in this work refers to the extent capacity is utilized and accounts for lack of input resource and or demand, and competition with complimentary technologies. It is same as Plant Load Factor. An integrated generation expansion planning and generation scheduling model, which is a Mixed Integer Linear Program (MILP), is formulated for which availability of the natural energy resources, i.e., from sun, wind and hydro, is exogenously specified at hourly time intervals. Hourly temporal resolution is needed to capture the variation in availability of both solar and wind energy. This multiyear generation expansion planning model incorporates operational details [16]: startups, ramping, and minimum output for generator groups. Implementation of this model has involved writing a programming script for the MILP, and characterization of technological alternatives, demand and supply resource profiles.

Finally, results from varying levels of renewable energy integration in the Indian electricity system are presented as an application of the approach. In summary, it is a renewable-based generation expansion problem setup. This section detailed open questions in this setup which are related to incorporating operational details, selection of input parameters related to variability in demand and supply and their harmonization. Moreover, to the best of our knowledge, no attempts have been made at studying the transition of Indian electricity system. Indian electricity system is the third largest electricity system in the world with an installed capacity of 344 GW and annual generation of 1306 GWh in 2017 [38]. Unlike the electricity systems in developed countries it is a rapidly growing system (capacity growth in last half century has been exponential) and the problems encountered while determining the planning requirements and other model inputs for such a system and their solution is one of the contributions of this paper.

3. Planning dynamic integration of renewable energy in a transitioning electricity system: Modelling approach

Schematic of the proposed approach for model-based planning of dynamic integration of renewable energy in an electricity system is depicted in Fig. 1. We begin with an appropriate mathematical abstraction of the physical electricity system, which permits us to query some if not all the questions raised above through MILP. We build on the state of the art to optimally plan electricity generation augmentation and generation scheduling with explicit representation of capacity utilization and, devise methods to arrive at model inputs from historic time series data of electricity demand and variable energy resource availability profiles. All the possible supply chain interventions tracking the transitions from energy resources to electricity at the bus bar form the inputs for the mathematical model. The output is the optimal set of electricity generation portfolio temporally matching the demand modelled by representative load curves. The criteria like costs, efficiency of

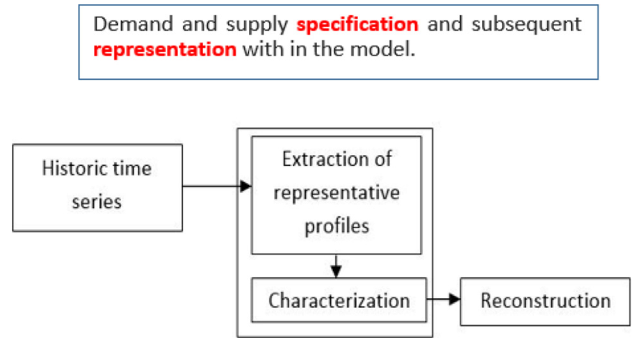

Fig. 2. Schematic representation of analytical procedures for developing demand and supply profiles.

transformation and emission coefficients form the basis for developing the optimal plan.

3.1. Modelling the dynamic supply and demand

The approach involves design and implementation of novel protocols to derive representative energy resource availability and demand profiles from historic time-series data. For reasons explained previously, our requirement is for: (1) demand projections for future years until the planning horizon, and, (2) representation of inter year demand variations. Unlike a typical forecasting problem, where we use patterns from past to predict the future, in this study we have an additional step of using exogenously specified demand forecasts for future years in addition to patterns extracted from past data. Inter year demand variations were available from past hourly load data [39]. The same data also captures the upward trend in demand across years. But this upward trend in past hourly data is not a good predictor of future demand because of prevalent deficits in Indian electricity system and widespread lack of access to electricity. Instead, we have used peak annual load projections from official Government of India report [40]. The broad approach adopted to derive these profiles is shown in Fig. 2. The objective is to first obtain the aggregate planning requirements, i.e., specification of annual demand for electricity and peak loads, and subsequently derive representative profiles, which capture the prevalent variations for the time till planning horizon. We work with historic electricity load curves and resource availability time series to extract representative profiles [41]. The method is discussed in detail in the sections presenting case study discussions.

3.2. Integrated generation expansion and generation scheduling model

There are successive requirements of technical feasibility (supply-

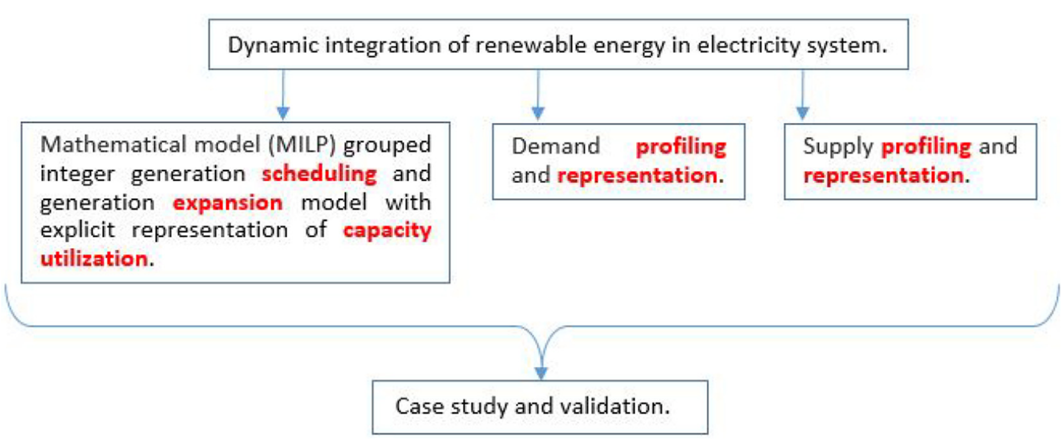

Fig. 1. Schematic of the proposed methodology.

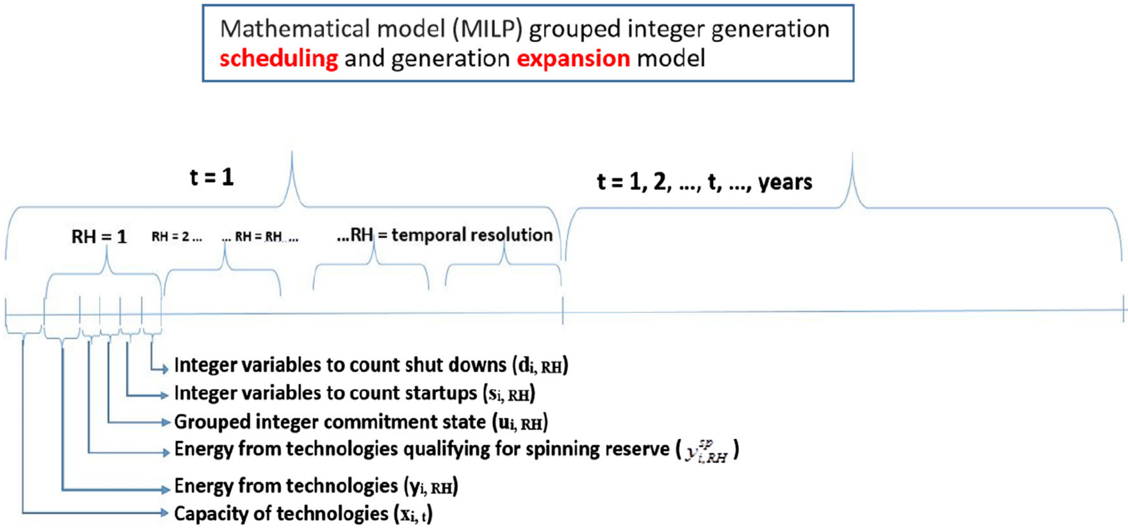

Fig. 3. Description of the decision vector of the mathematical model.

demand matching), resource availability, response to demand gradients, technology specific constraints (minimum load, startups) and finally the objective function (minimize cost or emissions) imposed on the electricity system. Here we unify, through algebraic formulation of the mathematical model, the different constraints to formulate the optimization problem. Schematic representation of the decision vector is as shown in Fig. 3 and is discussed in detail in later sections. The computer code for the model is written as a matrix generator in MATLAB and the decision vector provides a frame of reference for that.

We propose unit resource profile inversion loading of variable renewable energy dispatch variables to honor the capacity utilization for variable renewable generation capacity (Fig. 4). The need for this implementation and the method used are discussed subsequently. In absence of components from inverted unit resource profile, the solutions, as illustrated in Fig. 4, do not honor capacity utilization constraints. Without components from inverted unit resource profile, dispatch follows exogenously specified resource limits and flattens out as the capacity constraint is realized, effectively leading to an increased capacity utilization. The outcome of this approach is akin to having hourly resolution capacity factors used by [31].

4. MILP for generation expansion and generation scheduling

Decision vector (Fig. 3) is constituted by long-term investment decisions and short-term operational decisions. The long-term decisions are the capacities of different technologies which are expected to be deployed at the beginning of each year and the short term operational decisions include quantum of electricity generation from the given technology portfolio and the startups and shut downs of several units of different technology types as applicable during the representative period. Subsequently for each representative hour, which together constitute the representative load curve, and, represent and account for the duration of the entire year-dispatch of power, i.e., generation output must equal the demand and spinning reserve. At each representative hour, the demand is specified in MW. Energy is computed as the aggregate of the demands at each of the representative hours weighted appropriately according to the duration they represent. The energy resource availability is specified for each representative hour, which constitute the representative profiles. Further three blocks (Fig. 3) at each representative hour are to keep track of scheduled units, startups and shut downs for generator categories. Variable renewable

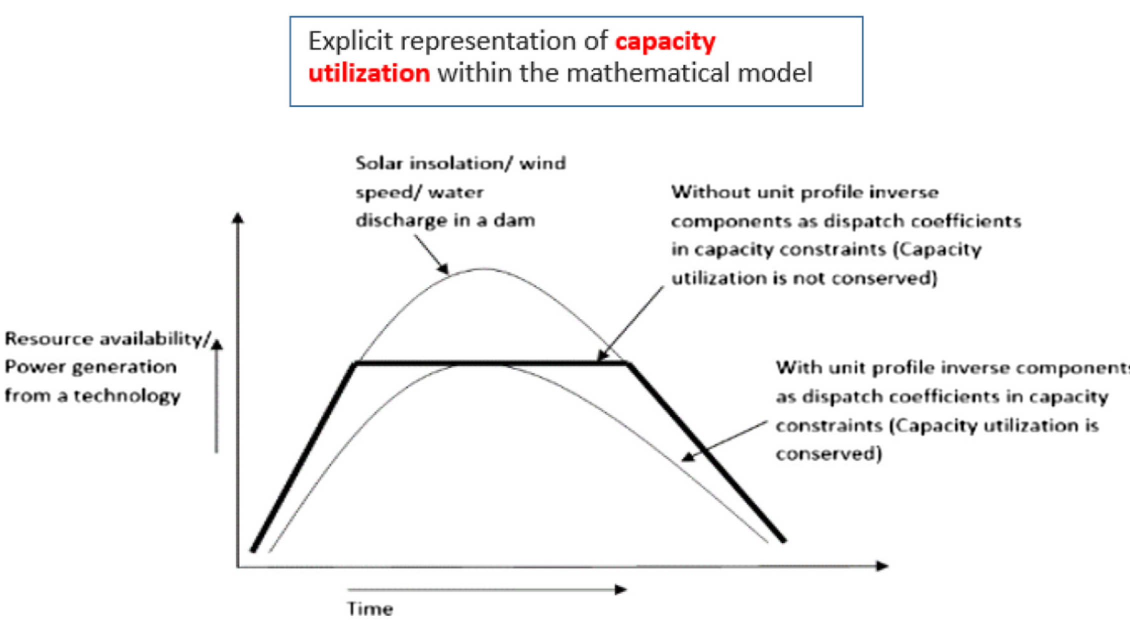

Fig. 4. Schematic of explicit representation of capacity utilization.

Table 1
Important terms and definitions.

Sl. No.	Term	Definition
1.	Representative hour (RH)	Each hour belongs to a representative profile which is representative of similar profiles occurring during that year.
2.	Gestation period for technology 'i' (g_i).	After the deployment decision is taken, it takes time for the technology to be available for operation. Gestation period is the delay from the time the decision for the capacity addition of a technology is made till it becomes operational.
3.	Resource conversion efficiency (e_i^r)	This is the conversion factor between the exogenous energy resource and electricity output. If the resource availability is already in terms of MW this is set to 1.
4.	Reserve margin	Reserve margin is a measure of available capacity over and above the capacity needed to meet normal peak demand levels.
5.	Energy from technology 'i' which qualify for spinning reserve (y_i^{sp}).	These variables are defined to enforce the spinning reserve constraints.
6.	Transmission and distribution coefficient for technology 'i' (tr_i).	Generation from technologies to meet the demand is attenuated due to transmission and distribution losses.

energy capacity moderates its output according to the energy resource availability, i.e., solar goes off every night. Table 1 lists important terms with definitions, which are relevant for MILP. Code for this model was written as a matrix generator in MATLAB and is available as appendix in [42].

4.1. List of indices and variables

Indices

I	index for electricity generating technologies.
r	index for resource categories.
RH	index for representative hours for a year.
t	index for years.

Variables and parameters

T	total number of years. This is the planning horizon.
L_i	life time of technology 'i' in years.
A_i	Availability factor (proportion available) for technology 'i'. It accounts for downtime (for maintenance) and is distinct from capacity utilization.
g_i	gestation period for technology 'i'.
o_i	operational life of technology 'i' in years. Technology can dispatch during its operational life only.
L_i	$g_i + o_i$. Total life of a technology is the sum total of the gestation period and the operational life.
D_{RH}	demand at representative hour 'RH' (MW).
D_t	peak demand for year 't'.
E_{RH}^r	availability of 'r'th resource in hour 'RH'.
cv_i	cost of supply through technology 'i' (Rs/kWh).
cf_i	capital cost of technology 'i' (Rs/MW).
S_i^{start}	unit startup cost for technology 'i' (Rs).
e_i^r	resource conversion efficiency of technology 'I', running on resource 'r'.
x_i^r	capacity of technology 'i', running on resource 'r' (MW).
x_i^{RM}	capacity of technology 'i' which qualify for reserve margin (MW).
y_i^r	energy from technology 'i', running on resource 'r'. This value is non-zero if the technology is operational (MWh).
y_i^{sp}	energy from technology 'i' which qualify for spinning reserve (MWh).
tr_i	transmission and distribution coefficient for technology 'i'.
$u_{i,\ RH}$	number of units of technology type 'i' scheduled during representative hour 'RH'.
$s_{i,\ RH}$	number of units of technology type 'i' started in representative hour 'RH'.
$d_{i,\ RH}$	number of units of technology type 'i' shut down during representative hour 'RH'.
U_i	unit size for technology 'i' (MW).
y_i^{min}	minimum output from technology 'i'.
$I_{i,\ RH}$	technology capacity in operational life at hour 'RH'.
R_t	Reserve margin for year 't'.
S_{RH}	spinning reserve for hour 'RH'. This has been detailed above.
Δ_i^{up}	Quantum of increase allowed in generation between two consecutive hours from technology 'i' (MW/unit time).
Δ_i^{down}	Quantum of decrease allowed in generation from a unit capacity of technology 'i' between two consecutive hours (MW/unit time).

4.2. Objective function

$$\text{Minimize}\left(\sum_t discount\ \text{factor}_t\left(\sum_{RH}\sum_t (cv_i y_{i,RH,t} + cv_i y_{i,RH,t}^{sp} + s_{i,RH,t} S_i^{start})\right) + cf_i x_{i,t}\right) \tag{1}$$

Objective is to minimize the total cost that includes installation, generation and startup costs.

4.3. Model constraints

Demand constraint: Dispatch of power, i.e., generation output from all generation technologies should be greater than or equal to the demand. Demand at each temporal point across all the years till the planning horizon is exogenously specified.

$$\sum_i y_{i,RH}\, tr_i \geqslant D_{RH}\,(\text{in MW}) \tag{2}$$

Further, there is requirement of reserves to cater to system contingencies. The need for reserves is split into categories depending on the time scale, i.e., short term spinning reserve and long-term reserve margin. Spinning reserve is computed as 5%[1] of the demand at each of the temporal points.

$$\sum_i y_{i,RH}^{sp}\, tr_i \geqslant .05*D_{RH} \tag{3}$$

Reserve margin is 15% [43] of the peak demand for each year 't'. The firm peak capacity credit for wind is taken as 10% of installed capacity [16]. Solar capacity is not considered for reserve margin.

$$\sum_i x_{i,t}^{RM} \geqslant 1.15*D_t \tag{4}$$

Resource constraints: At each temporal point aggregate dispatch from technologies running on a common resource must be less than the availability of that resource. Energy resource availability at each temporal point must be specified exogenously. Such inputs could either be generated based on the weather information or from historic data.

[1] Taken from the National Electricity Plan [43].

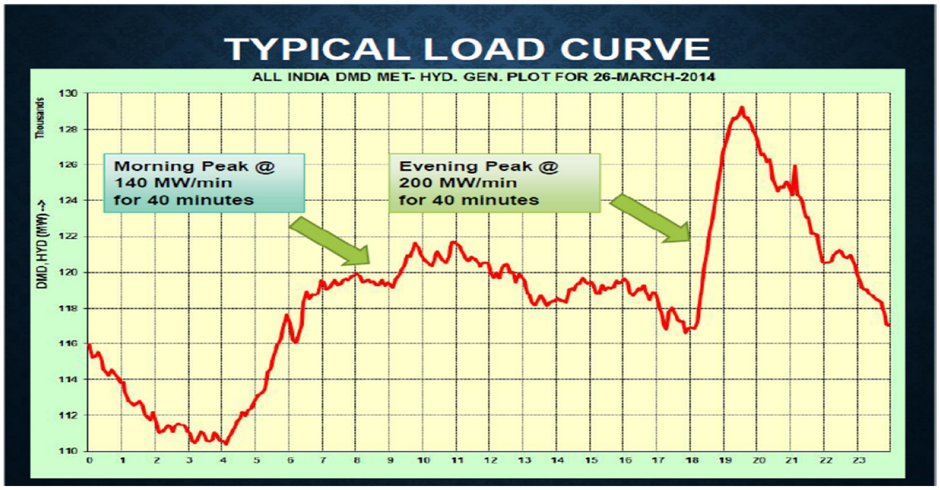

Fig. 5. Peaks and ramps in all India load curve. Source: Southern Regional Load Dispatch Centre, 2014.

$$\sum_i (y^r_{i,RH} + y^{sp,r}_{i,RH}) e_i \leqslant$$

$$E^r_{RH} \text{ Summation is over technologies running with same resource} \tag{5}$$

Capacity constraints with gestation and replacement: Number of scheduled units for every technology category has to be less than total installed capacity. After the deployment decision is made, it takes time for the technology to be available for operation. Gestation period is the delay from the time the decision for the capacity addition is made till it becomes operational. Total scheduled capacity of type 'i' at hour 'RH' has to be less than the total capacity of type 'i' in operational life at that hour (Eq. (6)). Number of startups at any time are less than total installed units which are in operational life (Eq. (7)).

$$u_{i,RH} U_i \le I_{i,RH} \tag{6}$$

$$s_{i,RH} U_i \le I_{i,RH} \tag{7}$$

Installed number of units are computed endogenously by the model. There is a time difference between a consecutive shut down and start up. Depending on the technology the time difference can range from few hours to few weeks. To account for this, right hand side of Eq. (7) must be adjusted to account for shut downs in the preceding hours.

For technologies, which are deployed in certain unit sizes, dispatch cannot be more than the maximum output from the available scheduled units at that time, where availability is represented through availability factor.

$$A_i u_{i,RH} U_i \geqslant y_{i,RH} + y^{sp}_{i,RH} \tag{8}$$

Also, there is a lower bound on the dispatch from technologies with minimum output constraint, i.e., dispatch from those units should be more than minimum output level of scheduled units.

$$y_{i,RH} + y^{sp}_{i,RH} \geqslant y^{\min}_i u_i \tag{9}$$

Only capacities past their gestation period can contribute to the dispatch from that category of technology.

$$\sum_1^{RH} x_{i,\,RH-g_i} \geqslant y_{i,\,RH} + y^{sp}_{i,RH}\, \text{If}(RH-g_i) \leqslant 0,\ \ y_i = 0; \tag{10}$$

Dispatch from technology 'i' should be less than the installed capacity, which is in operational life.

$$\sum_1^{RH} x_{i,\,RH-o_i} \geqslant y_{i,\,RH} + y^{sp}_{i,RH}\, \text{If}(RH-o_i) \leqslant 0\ y_i = 0 \tag{11}$$

Generation state equation: The number of generating units at each hour are calculated as the sum of startups in the current hour and the number of scheduled units in the previous hour minus the shut downs in the current hour.

$$u_{i,RH} = u_{i,RH-1} + s_{i,RH} - u_{i,RH} \tag{12}$$

Ramp constraints: These refer to the possible increase/decrease in generation between two consecutive hours from technology 'i' (MW/unit time).

$$y_{i,RH+1} + y^{sp}_{i,RH+1} - y_{i,RH} - y^{sp}_{i,RH} \leqslant u_{i,RH} \Delta^{up}_i U_i + s_{i,RH+1} U_i \tag{13}$$

$$y_{i,RH-1} + y^{sp}_{i,RH-1} - y_{i,RH} - y^{sp}_{i,RH} \leqslant u_{i,RH} \Delta^{down}_i U_i + d_{i,RH} U_i \tag{14}$$

5. Developing supply and demand profiles: Case of Indian electricity system

Specific to India, renewable energy capacity additions and generation from wind and solar, have increased substantially during past few years and form a significant proportion of the total generation in the grid. All India installed capacity as on June 2018 was 343,898 MW, which included 69,022 MW of renewable energy capacity [38]. It can no longer be called marginal capacity and serious thought needs to be given to balance the variability of generation from this capacity [45,46]. To instantiate the problems arising from variability in renewable generation, Fig. 5 depicts the all India typical load curve, which peaks in the morning and evening. Ramp up, i.e., upward change during the evening peak is steep, i.e., 8000 MW compared to the morning ramp up of 5600 MW within 40 min. With increasing grid integration of wind and solar, the ramps both in upward and downward directions are expected to become steeper.

Thus, both demand for electricity and renewable energy resource availability vary temporally. Therefore, any aggregate estimates of demand and resource potential are inadequate as inputs to any planning model (such as the above), and the need arises for capturing the dynamic variations as stated above. The dynamic variations in renewable resources and electricity demand are modelled using resource availability as well as demand profiles. Given these profiles, the planning problem essentially is to compute the capacity (MW) of and generation (MWh) from each technology such that the electricity system is feasible, i.e., supply meets demand, resource availability, ramping constraints and capacity utilization constraints are honored, and the stated objective is met, i.e., cost or emissions are minimized.

5.1. Technology characterization

Electricity generating technologies are distinguishable from each other in terms of economic attributes: capital costs, operational costs;

Table 2
Technology characterization.
Sources: [48,49,52].

	Unit size (MW)	Ramp rates (MW/hr)	Startup cost (Million Rs.)	Minimum load	Spinning reserve	Reserve margin	Capital cost (Million Rs/MW)	Annual fixed cost (Million Rs/MW)	Variable cost (Rs/kWh)	Plant life (Years)	CO_2 eq (gm/kWh)
Diesel generator	25	25	0.26	10	Yes	No	37	1.7	10.49	20	778
Oil steam	300	100	1.9	363	Yes	Yes	75.9	1.5	0.89	30	778
Gas steam	400	200	1.5	100	Yes	No	80.2	1.5	2.21	30	443
Coal	500	135	1.7	275	Yes	Yes	50.8	1.6	0.96	30	970
PHWR-Nuclear	700	80	1.9	385	Yes	Yes	99.2	10.6	0.51	40	66
Solar CSP	Any	0	0	0	No	No	120	1.8	0.00	25	48
Wind offshore	Any	0	0	0	No	10%	185.8	10.4	0.00	20	0
Large hydro	300	150	0	0	Yes	Yes	82.7	3.3	0.00	40	10
Biomass gasifier	Any	0	0	0	No	No	44.2	4.7	4.06	20	20
Micro gas turbine	Any	0	0	0	No	No	55.8	3.3	2.21	20	443
Solar PV	Any	0	0	0	No	No	60.6	1.3	0.00	25	0
Wind onshore	Any	0	0	0	No	10%	61.9	1.1	0.00	20	0
Biomass steam	Any	0	0	0	No	Yes	60	4.5	4.06	20	20
Biogas, Landfill gas	Any	0	0	0	No	Yes	88.5	4.7	4.06	20	10

environmental attributes: emissions, water use; and technical attributes: minimum loads, ramp rates. These attributes are associated with energy technology capacity and/or generation output from the technology. Based on taxonomy of energy technology characterization [47–51], we understand that they differ in terms of: (a) Set of technologies, i.e., electricity generating technologies under consideration (b) Number and variety of characterizing attributes, (c) Attribute measurements: subjective or empirical and (d) Range of attribute measurements. The required data for characterization of different energy technologies are obtained from various secondary sources. The capital cost, operational cost, heat content, conversion efficiency and emissions data are compiled from Central Electricity Regulatory Commission [52], Central Electricity Authority [53,54], ESMAP [48], NITI Aayog [10]. Operating constraints such as minimum outputs, ramp limits were obtained from data catalogues released by national energy agencies [48,49]. Technology characterization output is presented in Table 2 and it forms an input for model validation. Capital cost is the cost at time of commissioning and includes overnight cost of construction with interest.

5.2. Demand profiling

Demand for electricity varies with time and this variation in consumption pattern is due to several factors, e.g., time of the day, economic structure, consumer behavior, lifestyles, weather, diffusion of appliances, etc. For an electricity system, with deficits, e.g., India alongside these intra year variations there is an inter year increase in the supply to reduce the unmet demand. Indian electricity system is in a transient state with deficits that are due to prevailing low access levels and low per capita consumption. That is to say there are two kinds of deficits in case of Indian electricity system (i) Supply deficits (energy and capacity shortages and peak demand shortages), and (ii) Demand deficits leading to low access levels and low per capita consumption [19].

5.2.1. Estimating annual peak demand (GW) and demand for electricity (GWh)

The 18th electric power survey conducted by the Central Electricity Authority, Government of India has estimated annual peak load and total energy demand from 2011–12 to 2031–32 (Table 3) in intervals of 5 years [40]. For modelling, we have used linear interpolation – which preserves the peak duration factor (annual energy consumption/peak load) - between the 5-year intervals as provided by [40] to obtain annual peak load and energy demand. Peak duration factor for projections is approximately 6700 h.

Table 3
Long term forecast of electricity requirement for India.
Source: [40].

Year	Electricity (GWh)	Peak Demand (MW)
2011–12	904,012	124,995
2016–17	1,354,874	199,540
2021–22	1,904,861	283,470
2026–27	2,710,058	400,705
2031–32	3,710,083	541,823

The expansion planning is for meeting the incremental demand (both peak demand and annual demand for energy) over and above that is met by the existing installed capacity. The incremental demand has two components – first one is due to the growth in demand, and the second component is due to the retirement of existing capacity.

5.2.2. Estimating annual retiring capacity and incremental demand

The existing generation assets operate to meet the prevailing demand. In the face of increasing and unmet demand, India has to plan for additional generation capacity. The national electricity plan [54] developed as part of the 12th Five-year plan of government of India stipulates for retirement of 4000 MW during the period 2012–17 and another 4000 MW for 13th Five-year plan. We have obtained the planning requirements through superimposition of the retirement schedule of the existing capacity on the demand projections [40]. Following relations are used for deriving these estimates.

$$\text{Peak duration factor} = \frac{\text{Annual energy demand}}{\text{Annual peak load}}$$

$$\text{Capacity utilization (duration) factor} = \frac{\text{Annual energy demand}}{\text{Installed capacity}}$$

Incremental energy required = Projected energy requirement − Energy demand met by existing supply
Demand for energy on account of retiring capacity = Retiring capacity * Capacity utilization factor
Effective energy demand = Incremental energy demand + Energy

demand on account of retiring capacity

$$\text{Effective peak load} = \frac{\text{Effective demand for energy}}{\text{Peak duration factor}}$$

In absence of a detailed retirement plan, beyond the year 2022, a linear trend in retirement of existing capacity which culminates with complete retirement of existing capacity by 2055 is assumed. The aggregated retirement is assumed to be distributed amongst the technologies in proportion to their energy fractions.

5.2.3. Demand profiles (load curves)

The hourly variations in demand are largely due to differences in consumer behavior, practices, life style, working hours, industry operations, business hours, end-use needs, residential use patterns, etc., among different consuming sectors. The variations could be hourly, daily, weekly, monthly, seasonally (winter is different from summer, festival seasons), annually, etc. The inter-hour dynamics in load curves for any year represents all these influences. As far as capturing these operational dynamics in a multiyear strategic planning exercise is concerned, an exhaustive hourly resolution is computationally expensive. The solution lies in modelling the intra year variations with representative set of load curves at a finer resolution, i.e., hourly, bi-hourly, etc. So, the demand for a year is specified in terms of representative hourly load curves [41] of certain shapes and are derived from the historic data by adopting clustering approach. Clustering means partitioning a data set into a set of C clusters and a widely adopted definition of optimal clustering is a partitioning that minimizes distances within and maximizes distances between clusters [55]. There are papers, which provide a detailed review of techniques used for clustering load curves, e.g., k-means, minimum variance criterion, self-organizing maps, fuzzy C-means, support vector clustering etc. and show the impact of cluster formulation parameters on clustering validity indicators, e.g., clustering dispersion indicator, intra and inter clustering index, similarity matrix indicator, modified Dunn index, etc. [56,57]. With increasing penetration of electricity and time varying nature of electricity demand, grouping of load curves to extract representative behavior to manage, plan and efficiently operate the power system has gained interest [41,55,56,58,59].

In this study, we have devised procedures (Fig. 2) to obtain a set of daily representative load profiles for future years using aggregate peak load and annual energy projections and representative profiles obtained from historic hourly data from February 2011 to January 2014, for which we did not find any precedent. Data was obtained from National Load Dispatch Centre (NLDC), which reports all India load variations in hourly intervals. Fig. 6 is a plot of chornoloigically arranged hourly electricity loads from February 2011 to January 2014. Along with intra year variations it depicts an upward trend in demand. Our requirement is to capture both inter and intra year variation, but our contention is that upward trend captured by this data is not a reliable predictor for future years. This is on account of power and energy deficits present in Indian electricity system and wide spread lack of electricity access.

The idea essentially is to capture the prominent variations (hourly, daily, weekly and seasonal) in a set of representative profiles of load curves and use this set to account for the entire period. So, the questions are: What constitutes a representative load profile, i.e., duration and resolution, and, how is this set of representative profiles determined? We have taken the duration of each representative profile to be of 24 h (a day). Daily load curves are the way demand is usually reported [41]. Next, different daily representative load profiles can be extracted by clustering in the yearly, seasonal and/or monthly groups of load curves, i.e., representative load profiles for each year, season and or month.

The hourly load data for three years during February 2011 to January 2014 provided a total of 1096 daily load curves, and showed an upward trend (Fig. 6), which is because of growth in demand. We have used k-means clustering algorithm to determine the clusters and three criteria (CalinskiHarabasz, DaviesBouldin and Silhouett) to determine the optimal number of clusters to be computed by k-means. We have used k-means because it is one of the most widely used unsupervised learning algorithms for clustering load curves [55]. While several techniques are available for clustering load curves, each with both strengths and shortcomings [41,60], k-means in combination with criteria to resolve bias (prediction) versus variance (accuracy) tradeoff to select optimal number of clusters satisfies our requirement of capturing the intra year variations. The representative load curves thus obtained are subsequently used for construction of future year load curves using peak load and annual energy projections for respective years. The peak load and annual energy projections are obtained from the official Government of India report [40]. Daily data at an hourly resolution is a vector in R^{24}, i.e., in 24-dimensional vector space. The steps followed in the clustering exercise are depicted in the flow diagram shown in Fig. 7. Out of the two pathways that we explored for clustering (Fig. 7) differencing (D_{RH}-D_{RH-1} $\forall$ RH ≠ 1) of load curves to eliminate the upward trend, followed by clustering 1095 difference curves together yielded better results compared to clustering yearly load curves separately. Following these steps, we have proceeded with two representative load profiles extracted from the hourly differences in the three-year pool, i.e., Feb 2011–Jan 2014 (Fig. 8).

Characterization of the extracted representative load profiles (Table 4) will be used for the reconstruction process, i.e., deriving representative load profiles from annual demand for energy and peak load for future years. Column 2 of Table 4 is a compilation of fraction of daily load curves classified as each of the two clusters and column 3 is the proportion of the total energy under each of the two profiles. The energy content under each profile is needed in our devised construction

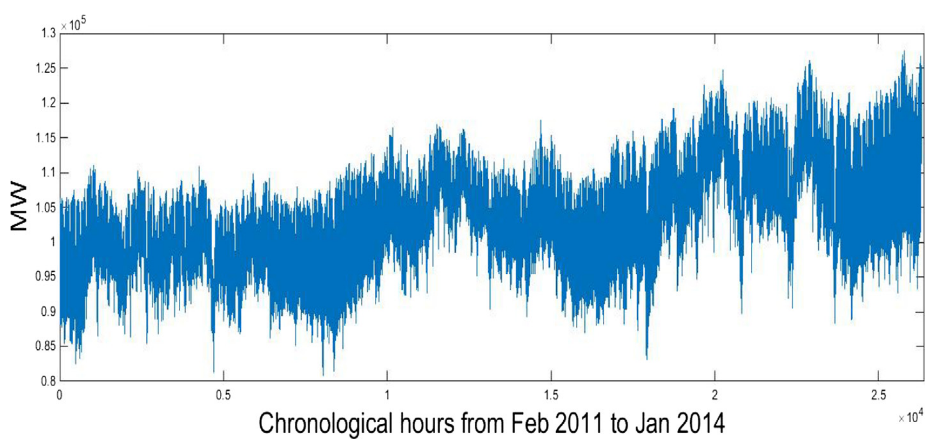

Fig. 6. hourly loads at all India resolution.

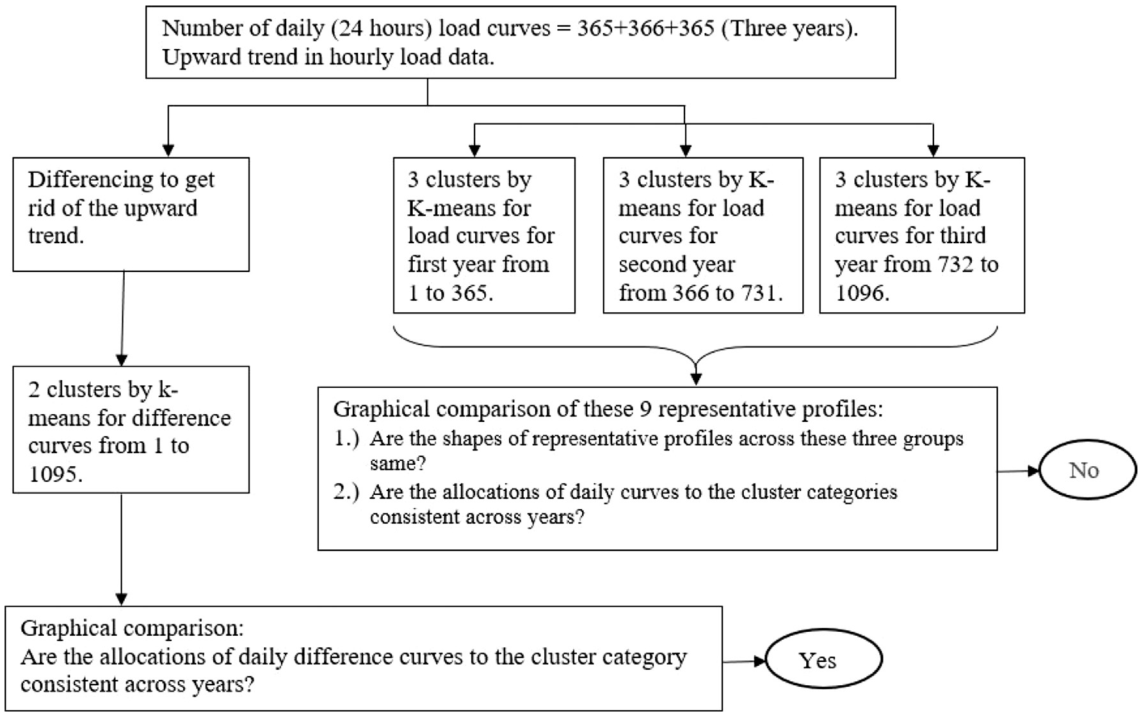

Fig. 7. Flow diagram of steps followed for clustering of load data.

process, which we discuss in subsequent sections.

The steps used in the construction of future load profiles are outlined in Fig. 9. We obtain the annual demand for energy and peak loads for future years as explained in previous sections. The next steps in construction are deriving representative load curves for future years using the estimated annual demand for energy and peak load of those years and the extracted representative load curves. While doing this, we could either conserve peak deviation sum fractions, i.e., peak load minus each of the 24 discrete points constituting the representative load curve divided by total area under the curve from the historic representative load curves (Eq. (15)) or just the sum fractions, i.e., each of the 24 discrete points constituting the profile divided by the total area under the curve (Eq. (16)).

$$\frac{(x_{peak}^{reconstructed} - x_i^{reconstructed})}{\sum x_i^{reconstructed}} = \frac{(x_{peak}^{historic} - x_i^{historic})}{\sum x_i^{historic}} \tag{15}$$

$$\frac{x_i^{reconstructed}}{\sum x_i^{reconstructed}} = \frac{x_i^{historic}}{\sum x_i^{historic}} \tag{16}$$

Table 4
Characterization of load curves: load (load profile obtained by cumulative sum of differences with base = load at the first hour of the year).

	Time fraction of annual occurrence (a)	Relative area under the curve (b)	Peak duration factor (c)	Effective energy (a * b/Σa * b)
RLC 1	0.501	0.516	0.913	0.519
RLC 2	0.499	0.481	0.936	0.481

By using Eq. (16), the annual demand for energy is conserved but the peak loads in constructed representative load curves are consistently below the estimated peak loads. This discrepancy is because of different peak load factor for the representative load curves obtained from the historic data, and the future projections of annual demand for energy and peak load. For the same reason, if estimated peak loads for future years are conserved in the reconstruction process (Eq. (15)), the annual demand for energy is overestimated. We have used Eq. (15), which is in line with the pragmatic planning philosophy that it is better

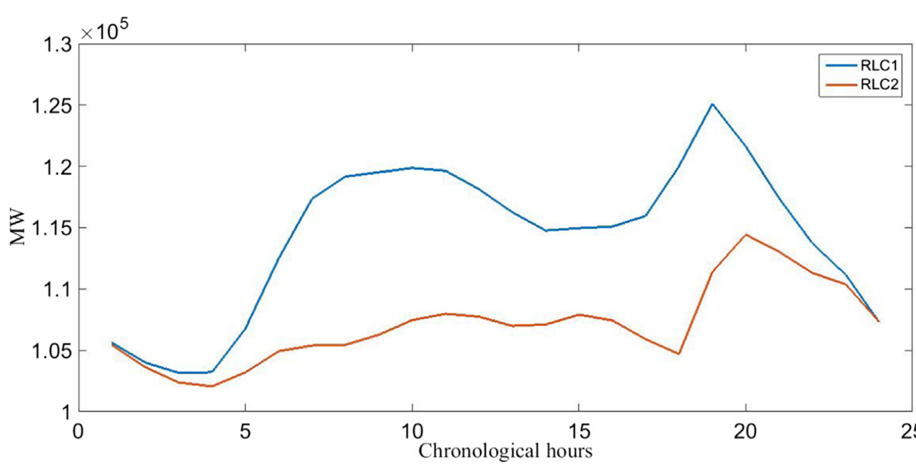

Fig. 8. Representative profiles.

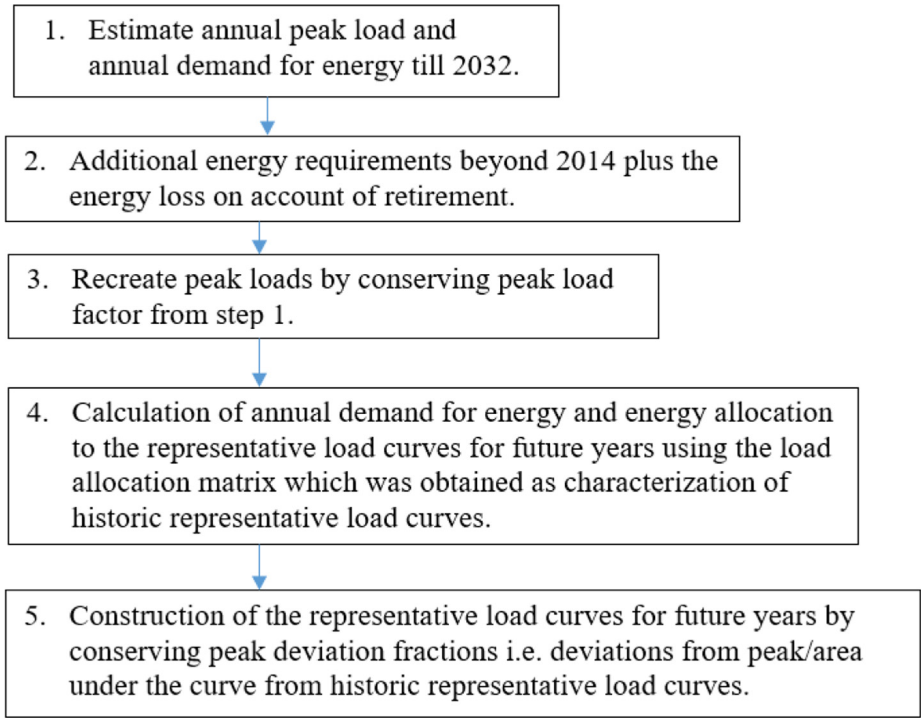

Fig. 9. Schematic of steps followed to obtain load profiles.

to overestimate the requirements and underestimate the resources than vice versa.

5.3. Estimating resource availability

Depending on type of technologies adopted, power generation plants require different energy resources to generate electricity. Generation technologies for this case study (Table 2) fall in 10 resource categories: diesel, fuel oil, gas, coal, nuclear fuel, solar, wind, biomass, biogas and hydro. Prospecting of energy resources, i.e., how much energy resource is available at which location and at what time is nuanced involving multitude of considerations ranging from natural availability to the limitations imposed by economic factors, i.e., viability and social feasibility. Availability of conventional energy resources does not vary on short time scales, i.e., on hourly or daily basis. However, there are variations in availability of renewable resources: Solar, Wind, and Hydro. Availability of these resources is influenced by natural factors and has a temporal profile, which varies across regions.

5.3.1. Variable renewable energy resources

For solar, wind and hydro generation in India, assuming the peak generation output to be equal to the installed capacity, the capacity utilization rates are estimated, using the data collected from NLDC at 20%, 30% and 50% respectively, but since the peak generation output is not same as the peak capacity, replacing the peak generation output with the installed capacity[2] [61], capacity utilization is estimated at 15.41%, 13%[3,4] and 40% respectively, which are low. Because of discrepancy in the reported [62–64] and observed values of capacity utilization for wind and solar, we consider their capacity utilization to be 25% and 19% respectively.

5.3.2. Unit profile inversion

To ensure that capacity utilization constraints for wind, solar and hydro are honored in MILP we have used unit profiles, i.e., temporal intra year variations for a unit capacity, which we extract from the historic data, to populate the capacity constraints for wind, solar and hydro capacity. Except for when the peak is realized and unit profile value is same as ratio of installed capacity and peak generation, all other values in unit profile are below this ratio. The point wise inverse of this unit profile when multiplied to dispatch variables at respective temporal points ensures that capacity utilization is preserved.

Without unit profile inversion components, the energy dispatch follows the exogenously specified energy resource limits and flattens out as the capacity constraint is realized, effectively leading to misrepresentation of capacity utilization (Fig. 4). The representative resource profiles are obtained from historic data. Like the process adopted for construction of representative load curves from future year estimates of energy demand and peak load, resource profiles are extracted from exogenously specified upper limits on capacity.

5.3.3. Resource availability profiles

The approach used for generating future resource profiles is like that used for developing current as well as future representative load profiles (Fig. 9). These profiles are developed from the anticipated installed capacity additions (Fig. 10), which serve as upper limits on capacity deployment endogenously computed by the model. This is because energy resource availability for wind, solar and hydro is reported in terms of peak deployable capacity (MW).

5.3.4. Wind power generation profiles

Fig. 11 shows a plot of all India wind power generation at 15-min intervals in 2014 and the data is obtained from NLDC. This is used for extracting the representative wind energy availability profiles. Applying k-means clustering algorithm, two representative profiles for wind power generation are obtained. Fig. 12 shows these two daily representative wind availability profiles at 15-min resolution. Profile 1 is visibly higher than profile 2 with almost a constant difference of 3500 MW. But the high wind occurs only for 91 days out of 365 days in

[2] https://www.sldcguj.com/compdoc/Installed_capacity_30042015.pdf.

[3] It is estimated at 15% at https://en.wikipedia.org/wiki/Wind_power_in_India.

[4] Based on data from: http://globaldata.enerdata.net/global-energy/database/ it comes to 17.4%.

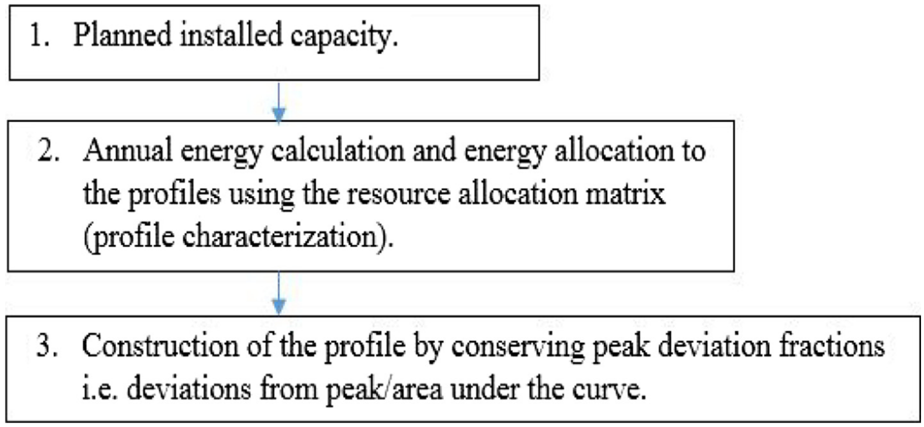

Fig. 10. Schematic of steps followed to obtain supply profiles.

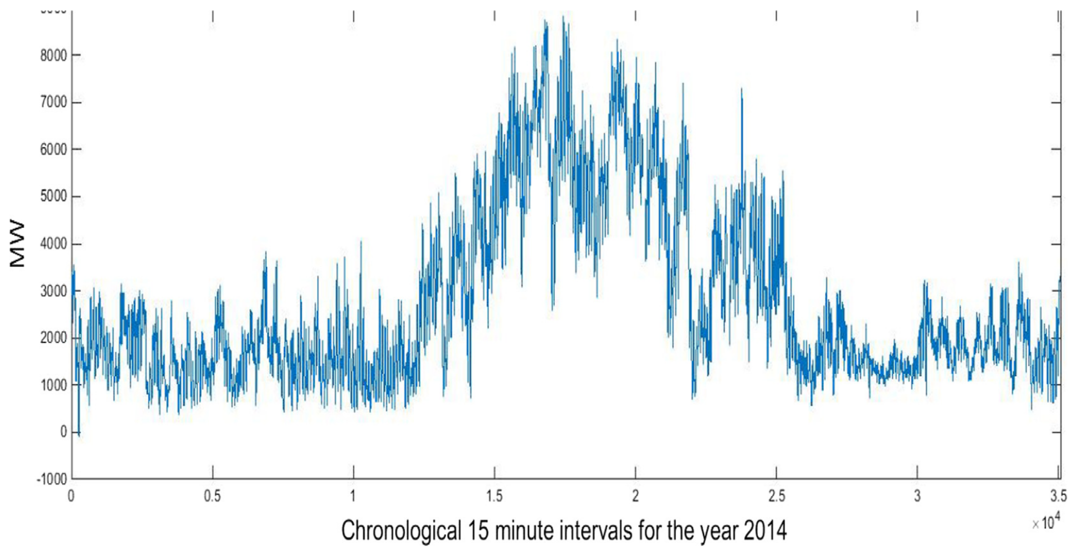

Fig. 11. Wind profile for India.
Source: [39].

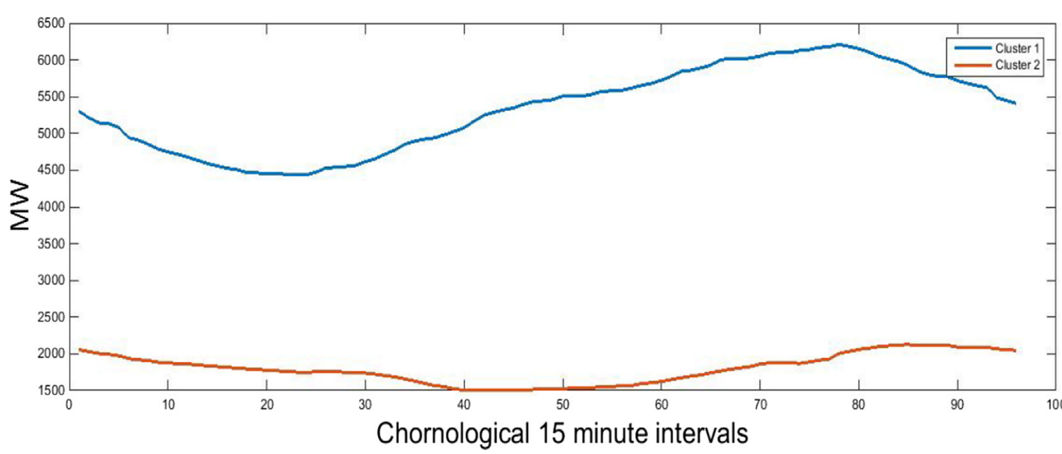

Fig. 12. Two representative profiles for wind power generation.

a year with the remaining being low wind days (Table 5). It is during middle of the year, i.e., June to August that India has high wind days, which also happens to be the monsoon season (Fig. 13).

Capacity utilization with these two representative profiles (Table 5) is 21.1%, which compared to the prevailing value of 15% is an overestimate. Consequently, we have tried increasing the number of clusters to check if they satisfy the capacity utilization constraint, and finally arrive at six clusters (Fig. 14) for wind, which are used in subsequent construction of future resource availability profiles and the unit profile.

Table 6 contains the details of the characterization of six extracted wind power profiles used in development of future profiles as outlined in Fig. 10. Annual energy (GWh) from the resource category is endogenously

Table 5
Allocation of daily wind power availability curves to clusters.

Cluster index	Instances (days) classified	Proportion of area under the representative profile
1	91	0.747
2	266	0.242

by the model.

5.3.5. Hydro power generation profile

Fig. 15 shows the plot of hourly variations in hydropower generation during 2008–2014 in India. Using the same set of criteria and approach as with demand data, we obtain three representative hydro power profiles.

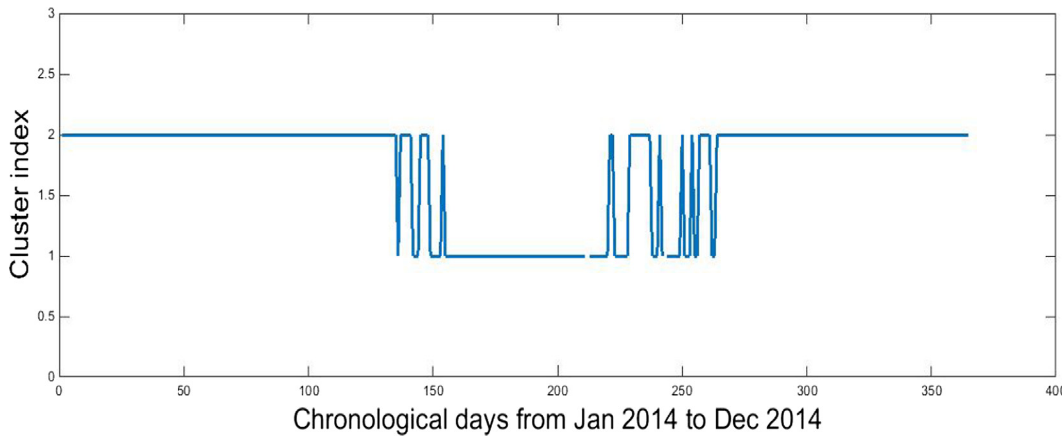

Fig. 13. Allocation of daily wind curves to clusters.

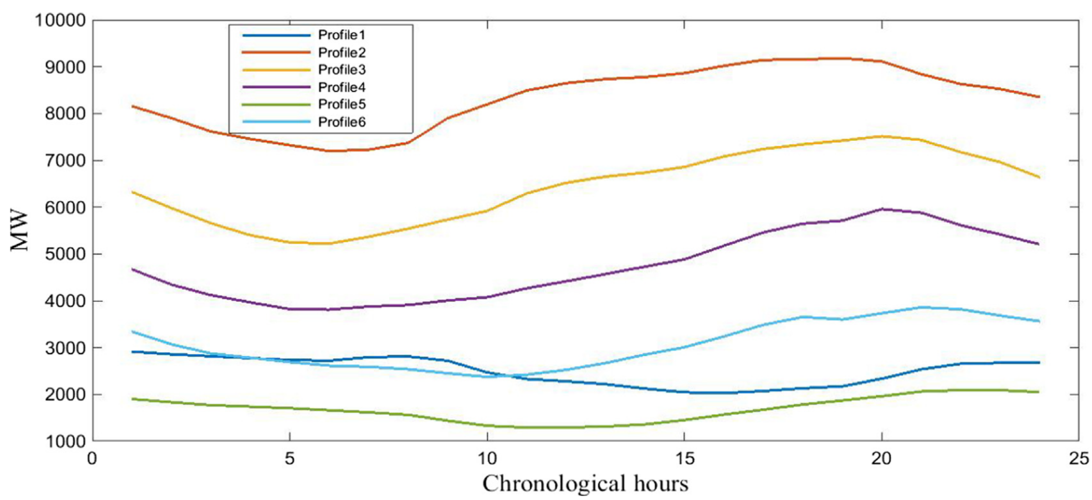

Fig. 14. Six representative profiles for wind power generation.

Table 6
Characterization of wind power availability (6 representative profiles).

Representative profile	Time fraction of annual occurrence (a)	Relative area under the curve (b)	Capacity duration factor (c)	Effective energy (a * b/ Σa * b)
1	0.252	0.093	0.117	0.196
2	0.082	0.312	0.391	0.213
3	0.085	0.240	0.302	0.170
4	0.082	0.177	0.222	0.121
5	0.414	0.063	0.079	0.217
6	0.085	0.114	0.143	0.081

calculated using the resource characterization matrices (Fig. 6). Effectively, in this construction of representative profiles for future availability of wind power (in MW), capacity values are conserved. This is because energy resource availability for wind is reported in terms of peak deployable capacity (MW). The representative profiles serve as upper limits on dispatch from capacity deployment which is endogenously computed

Representative hourly diurnal hydro profiles (Fig. 16) have almost similar shapes but differ in magnitude. It is safe to assume that India has high hydro days, medium hydro days and low hydro days, and every year they realize 49, 102 and 209 times respectively (Table 7), and are not necessarily consecutive (Fig. 17). As reported in Table 8, profile 3 (representative of cluster 3), i.e., high hydro day constitutes 45% of the cumulative energy (GWh) of all three profiles. Although, high hydro days are mostly in the months of April, May and June (Fig. 17). Beginning of the year and most of the later part of the year are low hydro days. High hydro days are hemmed by medium hydro days on both sides. Table 8 contains the characterization of three profiles used in the construction of hydro supply profiles for future years (Fig. 10).

5.3.6. Solar power generation profile

Fig. 18 is the plot of solar generation at 5-min intervals for one month for Gujrat obtained from NLDC and Table 9 contains the characterization of the two extracted profiles (Fig. 19). The India level data for solar generation was difficult to access, and since this was a validation attempt, we assumed the pattern of solar profiles from the state of Gujrat to be the same for India.

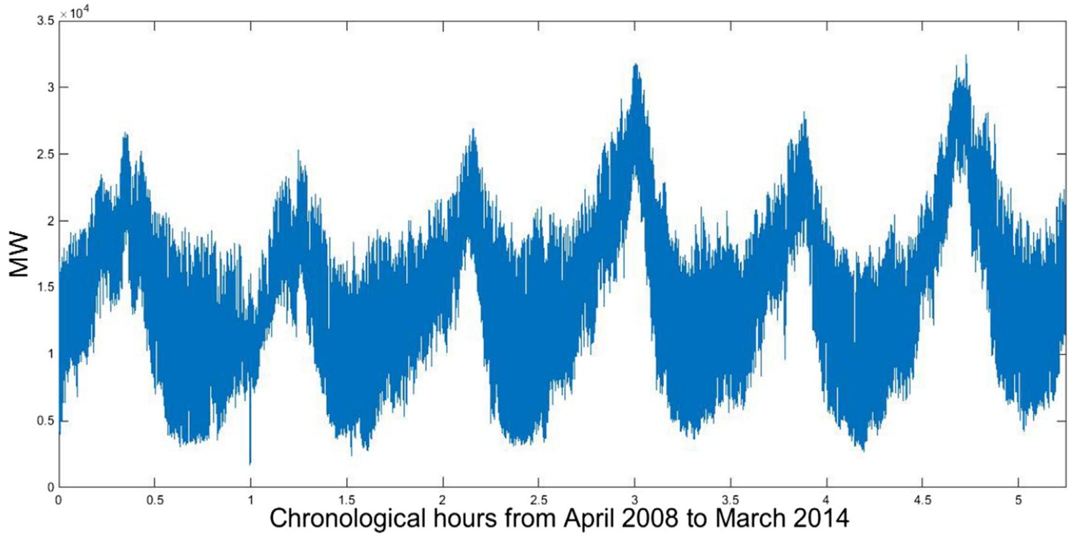

Fig. 15. Hydro power generation profile for India.
Source: [39].

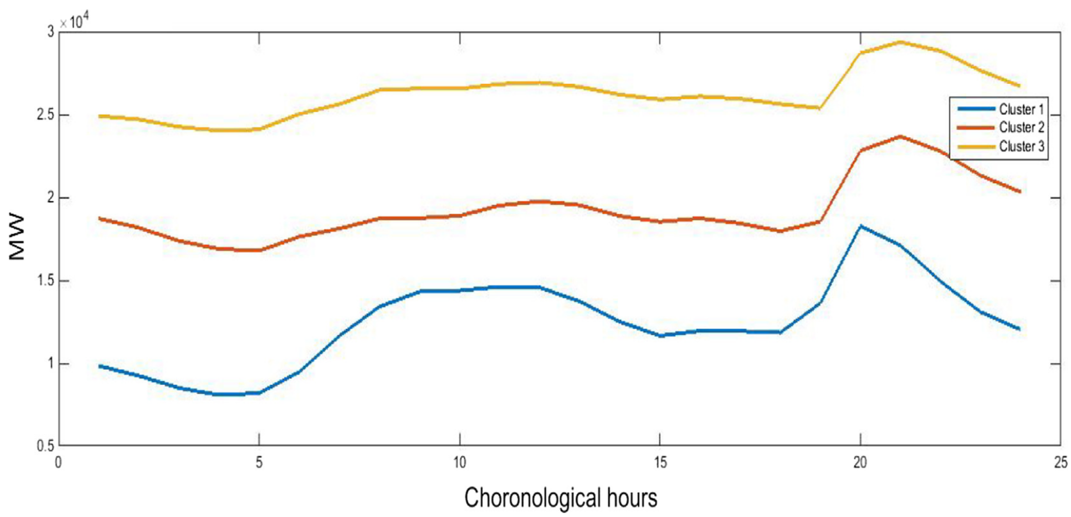

Fig. 16. Extracted representative hydro power profiles.

Table 7
Allocation of daily hydro power availability curves to clusters.

Cluster index	Instances classified	Proportion of area under the representative profiles
1	209	0.215
2	102	0.330
3	49	0.453

5.4. Harmonizing representative energy resource availability and load profiles

Having extracted the representative demand and energy resource availability profiles it is necessary to ensure their temporal alignment. To temporally align the representative load curves and energy resource availability profiles, we assign to each month, the maximally occurring cluster profile within that month (Table 10). This monthly assignment results in a workable temporal resolution, i.e., 7 profiles of 24-h duration each. Harmonizing for every day was resulting in a much higher temporal resolution and hence defeating the purpose of clustering in the first place. These monthly assignments do not impact the operational constrains which operate at inter-hour level. The aligned groups determine the temporal resolution of the model. This alignment creates a discrepancy in annual occurrence of load profiles when compared to actual cluster allocations. Annual time fractions for load cluster 1 and 2 are 0.50 and 0.49 in the actual cluster allocation (Table 4) and 0.42 and 0.58 after harmonizing (Table 11). And since the relative area under the two representative load cluster profiles is 0.52 and 0.48 respectively, the discrepancy in annual time fractions will result in minor underestimation of annual demand for energy. This is unlike the overestimation of annual energy demand, which occurred during the process of obtaining the load profiles for future years (Fig. 9). These two effects balance each other to some extent. We have used the former while validating the clusters and the later while generating model feeds. Harmonized groups of representative profiles after sorting are shown in Table 11.

We run the optimization model for a planning horizon of 18 years with 168 intra year points, i.e., seven hourly representative load curves. Among the two representative solar availability curves, the first is assumed to align with 2nd, 3rd, 5th and 7th groups, and the second with 1st, 4th and 6th groups.

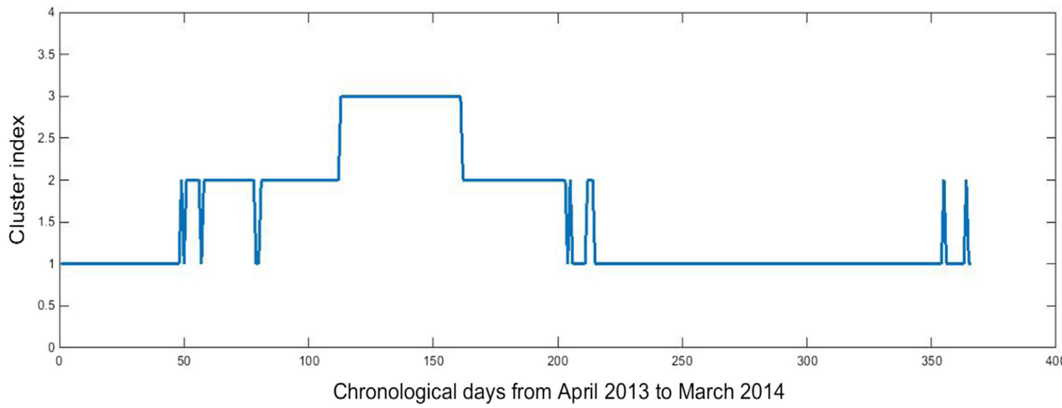

Fig. 17. Allocation of daily hydro power curves to clusters.

Table 8
Characterization of hydro power availability.

Representative profile	Time fraction of annual occurrence (a)	Relative area under the curve (b)	Capacity duration factor (c)	Effective energy (a * b/ Σa * b)
1	0.581	0.215	0.307	0.451
2	0.334	0.339	0.474	0.409
3	0.085	0.453	0.647	0.139

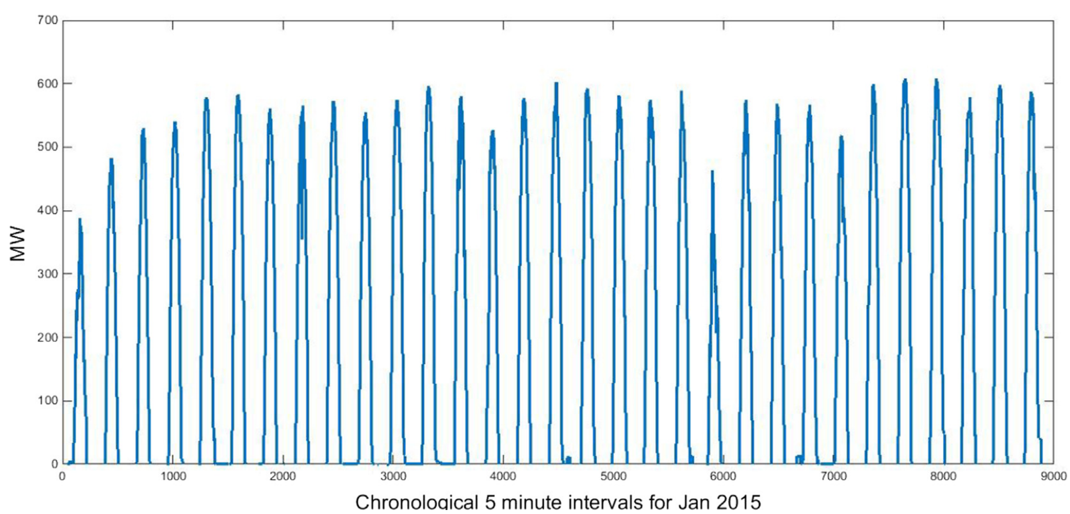

Fig. 18. Solar power generation profile for Gujrat.
Source: [39].

Table 9
Characterization of solar power availability.

Representative profile	Time fraction of annual occurrence (a)	Relative area under the curve (b)	Capacity duration factor (c)	Effective energy (a * b/ Σa * b)
1	0.499	0.611	0.178	0.61
2	0.501	0.389	0.113	0.39

5.5. Other inputs

All future cost estimates are discounted to their present values by using a discount rate of 9%. The other data used as input to the model are energy content of the fuels [65], conversion efficiencies [48] and resource availability [66]. Startup cost, with the exception of coal[5], in the absence of data is estimated as the product of unit size and variable cost. Discounted fixed operation and maintenance cost is factored into the fixed cost. We consider the electricity supply chain till the grid bus bar and hence tr_i (transmission and distribution coefficient for technology 'i') is uniformly 1 for the entire technology portfolio. The resource limits for Indian electricity system are as per NITI Aayog heroic effort scenario [67], however, the upper limit on wind energy capacity is 103 GW [44]. The base year used for the analysis is 2015 and we assume a linear trend in renewables share to values ranging from 5% to 40% by 2030 in total electricity generation from the additional capacity (Table 12). The baseline for comparison is 0% renewables share by 2030.

5.6. Model validation: case study findings and discussion

As stated earlier, this model-based approach is validated by using data from Indian national electricity system. Model is used to estimate the impacts of various levels of renewable energy (excluding hydro) integration on the Indian electricity system. To analyze the impacts, the integration levels are varied from 0% to 40% share of renewable electricity in total generation from additional capacity in 2030. The impacts

[5] Estimated from: http://www.cercind.gov.in/2013/whatsnew/Sop.pdf.

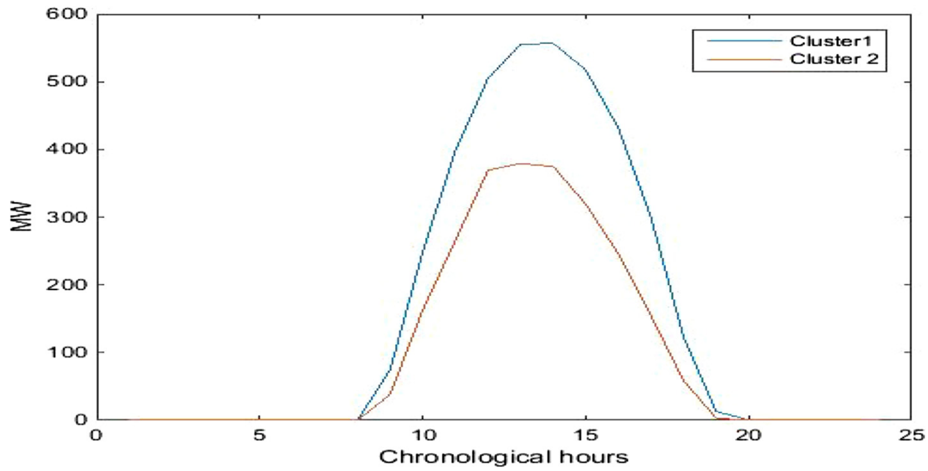

Fig. 19. Extracted representative solar power profiles.

Table 10
Harmonizing the representative load curves and representative supply curves.

Month of the year	Demand	Hydro	Wind	Aligned group
Jan	Cluster 1/2 (31, 0)	Cluster1/3 (31, 0, 0)	Cluster1/6 (19)	1–1–1
Feb	Cluster 2/2 (2, 26)	Cluster1/3 (28, 0, 0)	Cluster5/6 (19)	2–1–5
Mar	Cluster 2/2 (0, 31)	Cluster1/3 (29, 2, 0)	Cluster5/6 (19)	2–1–5
Apr	Cluster 2/2 (0, 30)	Cluster1/3 (30, 0, 0)	Cluster5/6 (22)	2–1–5
May	Cluster 2/2 (0, 31)	Cluster1/3 (20, 11, 0)	Cluster5/6 (11)	2–1–5
Jun	Cluster 2/2 (0, 30)	Cluster2/3 (2, 28, 0)	Cluster2/6 (16)	2–2–2
Jul	Cluster 2/2 (1, 30)	Cluster2/3 (0, 21, 10)	Cluster3/6 (16)	2–2–3
Aug	Cluster 2/2 (3, 28)	Cluster3/3 (0, 31, 31)	Cluster6/6 (9)	2–3–6
Sep	Cluster 1/2 (28, 2)	Cluster2/3 (0, 22, 8)	Cluster4/6 (14)	1–2–4
Oct	Cluster 1/2 (31, 0)	Cluster2/3 (7, 24, 0)	Cluster5/6 (19)	1–2–5
Nov	Cluster 1/2 (30, 0)	Cluster1/3 (30, 0, 0)	Cluster1/6 (16)	1–1–1
Dec	Cluster 1/2 (31, 0)	Cluster1/3 (31, 0, 0)	Cluster1/6 (16)	1–1–1

Note: Numbers in brackets are the number of days of that month which fell in respective cluster categories.

Table 11
Harmonized groups.

Sl. No.	Aligned groups of clusters in the order: demand-hydro-wind	Months of occurrence	Time fraction of annual occurrence
1	1–1–1	3 (Jan, Nov, Dec)	0.249
2	2–1–5	4 (Feb, Mar, Apr, May)	0.328
3	2–2–2	1 (Jun)	0.082
4	2–2–3	1 (Jul)	0.084
5	2–3–6	1 (Aug)	0.084
6	1–2–4	1 (Sep)	0.082
7	1–2–5	1 (Oct)	0.084

are assessed for a net generation (excluding the current generation) of 3129 TWh in 2030. The MILP model was generated in MATLAB 2014b and solved in GUROBI on a Z 820, Intel Xeon E5-2687 W Dual 8-core 3.10 GHz processor machine with 128 GB RAM. Size of the constraint matrix was roughly 100,000 by 200,000. The different problem instances took approximately 300 s, and the solver time was in the range of 50–10,000 s. In addition to what is reported here, extensive sensitivity analysis was performed by variations in input parameters [42] to sense check the model and validate whether the model solves the real-life problem correctly and gives a practical solution.

Summary of the results is presented in Table 12. To meet the net annual generation requirement of 3129 TWh, the installed capacity needed varies from a low of 534 GW with zero renewables to about 1135 GW with 40% renewables share in 2030 (Table 12). It is important to note that the installed capacity required more than doubles to meet same level of electricity generation. Another finding is that irrespective of increase in the penetration of renewable installed capacity, the conventional capacity that it substitutes remains at around 60 GW except at 5% penetration where 45 GW of renewable capacity replaces 33 GW of conventional capacity. This may be observed from substitution ratios given in Table 12, which suggest that to substitute one GW of conventional capacity, the renewable capacity need to vary from 1.4 GW to 11.4 GW at different penetration levels. Increasing share of solar capacity at higher penetration levels is the reason for such high substitution ratios (Fig. 21). To achieve a 40% renewable electricity share in total electricity generation, it is essential that about 58% of all the new installed capacity additions are renewable. This is also reflected in terms of sharp decline in overall capacity utilization from 66.9% at renewable energy share of 5% to just 31.5% at 40% share. In addition, startup costs as a fraction of total operating cost increases from 0.9% to 8.2% with increasing renewable share.

The total discounted cost (in 2015 Rupees), including the investment and operational costs, increase by just 50% for a transition from zero to 40% renewable electricity share in total electricity generation. However, the present value of the investment made in capacity expansion increases by 90% to achieve this transition. Almost negligible operational cost associated with renewable energy gives this total cost advantage. The benefit of this additional cost is the significant CO_2 mitigation that could be achieved. An electricity system with 40% renewable electricity share entails an annual saving of 0.58 $GtCO_2$, which is a reduction of 22% from the baseline emission (with 0% renewable electricity). The pertinent question is whether the substantial additional installed capacity required, cost incurred and generation efficiency lost is justified in terms of CO_2 mitigation achieved as a result of increased renewable energy penetration. It is a difficult question to respond to, however, the mitigation costs reported in Table 12 give some idea to

Table 12
Impact of renewable energy integration.

Indicators	Variations in indicators with changing levels of renewable energy integration					
Share of electricity generation from renewable energy (%)	None	5%	10%	20%	30%	40%
Generation from new installed capacity (TWh)	3129					
New installed capacity (GW)	534	546	598	776	953	1,135
Overall capacity utilization (%)	66.9	65.4	59.7	46	37.5	31.5
Renewable electricity generation (TWh)	0	165	327	626	926	1,226
Renewable installed capacity (GW)	0	45 (8%)	123 (21%)	301 (39%)	480 (50%)	659 (58%)
Substitution ratio (renewable capacity/Conventional capacity offset by renewable capacity addition)	NA	1.4	2.1	5.1	7.9	11.4
Present value of total additional cost (Trillion Rs.)	40.5	41.3	42.4	48.6	54.8	60.9
Present value of investment cost (Trillion Rs.)	22.8	23.1	24.5	30.8	37.1	43.3
Startup cost as fraction of operating cost (%)	0.9	1.1	1.2	1.8	4.6	8.2
Per unit cost (Rs./kWh)	2.95	3.01	3.11	3.61	4.02	4.56
Annual emissions in 2030 ($GtCO_2$)	2.62	2.60	2.55	2.32	2.18	2.04
Mitigation cost ($Rs./kgCO_2$)	NA	3.0	5.33	6.0	5.94	6.44
Per unit emissions ($kgCO_2/kWh$)	0.84	0.82	0.81	0.73	0.66	0.59

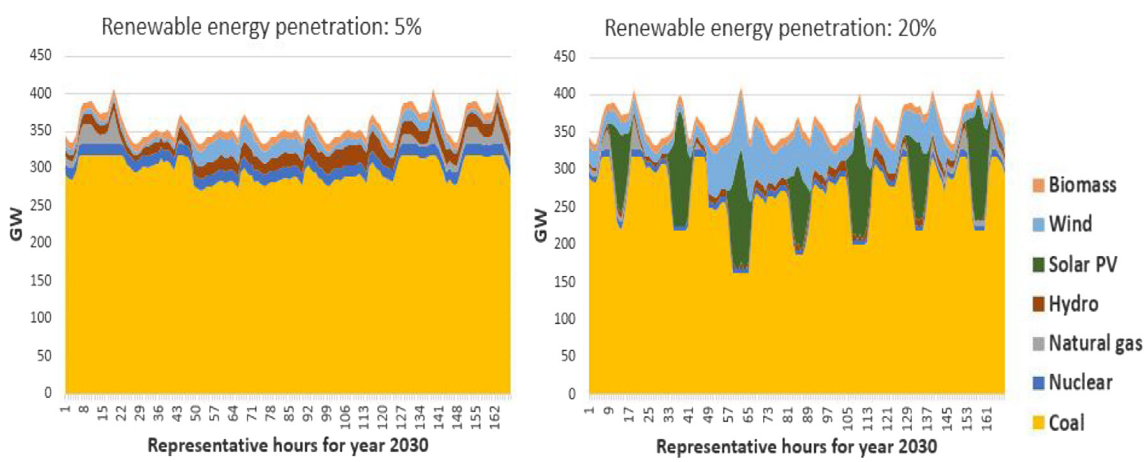

Fig. 20. Electricity dispatch with different levels of renewable energy penetration.

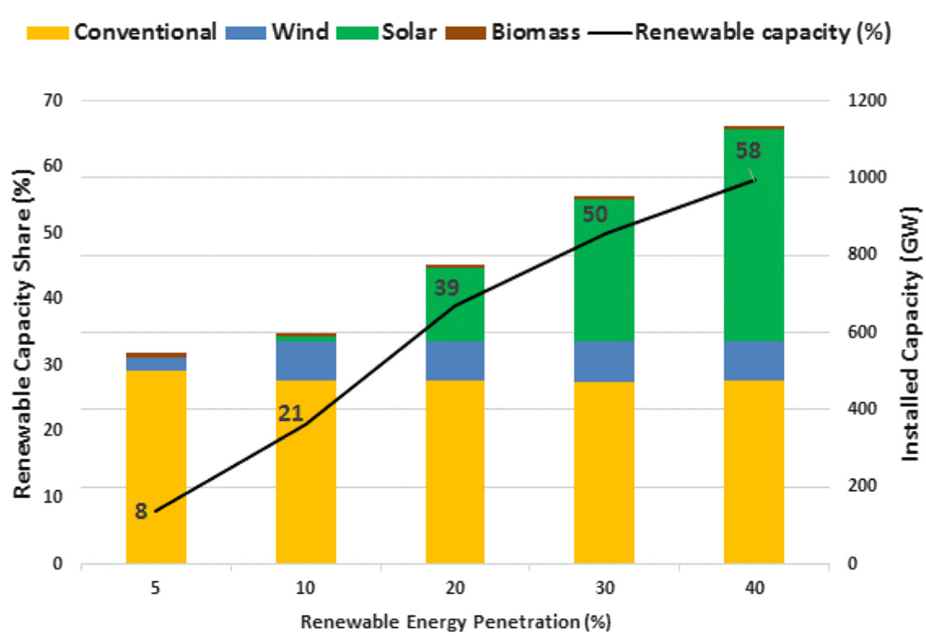

Fig. 21. Composition of renewable capacity with increasing renewable energy penetration.

take a rational decision. A comparison of these mitigation costs with the prevailing market prices for carbon certificates would be a logical step forward in making such decisions.

This renewable energy mainstreaming has some negative implications for conventional capacity. We may observe from Fig. 20 that the dispatch from solar and wind capacity transforms the net load curves (loads met by the conventional capacity) from a camel shape to a duck shape, which becomes more prominent with rising renewable

energy penetration levels. With the introduction of dispatch from wind and solar capacity, cycling of, i.e., number of startups and shutdowns of conventional electricity generators, will increase. Electricity generating units with faster ramping capability and lower startup costs, i.e., highly flexible options like natural gas generators, will be the preferred choices in such situations. However, the coal thermal systems are likely to face significant negative impacts due to loss of generation, frequent ramp downs, etc.

To ensure a given level of renewable electricity share in total electricity generation, renewable installed capacity share in total installed capacity has to be significantly higher (Fig. 21). This is due to the lower capacity utilization factors associated with renewable energy capacity. It may be observed from the figure that the conventional capacity almost remains at same level irrespective of renewable energy penetration levels. This observation is because of lean wind season. There is significant wind generation which offsets conventional generation during peak wind season but during the lean wind season conventional capacity is needed. From the above findings, we may conclude that renewable energy integration contributes to climate change mitigation and creates capacity redundancy in the system which calls for mechanisms to ensure viability for both conventional and renewable generation while ensuring reliability.

6. Conclusion

In this paper we have presented a model-based approach for planning dynamic integration of renewable energy in a transitioning electricity system. Building on the recent literature on power system modelling, this paper is a systematic exposition of how the important questions of supply side electricity generation portfolio concerning electricity system generation expansion can be queried. This approach enables better representation of renewable energy resource dynamics, which involved extracting load profiles for future years from aggregate projections and harmonizing them to ensure temporal correlations before feeding them into the generation expansion model with operational details. Study of the Indian electricity system to validate this approach presents itself as an interesting case given the aggressive transitions occurring. We find that increased penetration of renewable energy while bringing significant climate change benefits creates substantial capacity redundancy leading to lower capacity utilization of the system. This suggests need for implementing demand response strategies and mechanisms to ensure viability for both conventional and renewable generation while ensuring reliability. The findings provide indicative estimates of capacity additions, cost implications, GHG mitigation and losses in generation efficiency, which can inform the discourse on energy transition and climate mitigation.

The present model accounts for linear measures on capacity and dispatch, and further research is needed to incorporate spatial fluctuations and uncertainties in parameters, e.g., impacts of weather uncertainty, for better representation. Enforcing emission targets from Indian INDCs, and inclusion of carbon capture technologies will make for an interesting analysis and can be explored further. Nonetheless, we believe, stakeholders will find the process of enquiry presented here useful for investigation of the questions around generation expansion planning with renewable energy integration.

References

[1] Cecati C, Citro C, Siano P. Combined operations of renewable energy systems and responsive demand in a smart grid. IEEE Trans Sustainable Energy 2011;2(4):468–75.
[2] Sharma T, Balachandra P. IEEE International Conference on Industrial Engineering and Engineering Management. 2014. p. 637–41.
[3] Cochran J, Mai T, Bazilian M. Meta-analysis of high penetration renewable energy scenarios. Renw Sustain Energy Rev 2014;29:246–53.
[4] Alley R. Energy. Coursera: The Environment and Our Future; Feb 2014.
[5] Engeland K, Borga M, Creutin J, Francois B, Ramos M-H, Vidal J-P. Space-time variability of climate variables and intermittent renwable electricity production – a review. Renew Sustain Energy Rev 2017;79:600–17.
[6] Ma J, Silva V, Belhomme R, Kirshen DS, Ochoa LF. Evaluating and planning flexibility in sustainable power systems. IEEE Trans Sustainable Energy 2013;4(1):200–9.
[7] Shortt A, Kiviluoma J, Malley MO. Accommodating variability in generation planning. IEEE Trans Power Syst 2013;28(1):158–69.
[8] Amrutha AA, Mathirajan M, Balachandra P. A mathematical formulation for low carbon electricity planning in the presence of technology and policy interventions. In: IEEE international conference on industrial engineering and engineering management; 2014. p. 612–616.
[9] Huber M, Dimkova D, Hamacher T. Integration of wind and solar power in Europe: assessment of flexibility requirements. Energy 2014;69:236–46.
[10] IESS. India energy security scenario 2047; 2015. [Online]. Available: indiaenergy.gov.in/.
[11] Sharma T, Balachandra P. Benchmarking sustainability of Indian electricity system: an indicator approach. Appl Energy 2015;142:206–20.
[12] Lund DP, Lingren J, Mikkola J, Salpakari J. Review of energy system flexibility measures to enable high levels of variable renewable electricity. Renew Sustain Energy Rev 2015;45:785–807.
[13] Becker S, Frew BA, Andresen GB, Zeyer T, Schramm S, Greiner M, et al. Features of a fully renewable US electricity system: optimized mixes of wind and solar PV and transmission grid extensions. Energy 2014;72:443–58.
[14] Jacobson M, Delucchi M, Bauer Z. 100% Clean and renewable wind, water, and sunlight all-sector energy roadmaps for 139 countries of the world. Joule 2017;1:1–14.
[15] Howells M, Rogner H, Strachan N, Heaps C, Huntington H, Kypreos S, Hughes AEA. OSeMOSYS: the open source energy modelling system: an introduction to its ethos, structure and development. Energy Pol 2011;39(10):5850–70.
[16] Palmintier B, Webster M. Impact of unit commitment constraints on generation expansion planning with renewables. In: Power and energy society general meeting; 2011.
[17] Nehrir MH, Wang C, Strunz K, Aki H, Ramakumar R, Bing J, et al. A review of hybrid renewable/alternative energy systems for electric power generation: Configurations, control and applications. IEEE Trans Sustain Energy 2011;2(4):392–401.
[18] Motie S, Keynia F, Ranjbar M, Maleki A. Generation expansion planning by considering energy-efficiency programs in a competitive environment. Int J Electr Power Energy Syst 2016;80:109–18.
[19] Balachandra P, Chandru V. Supply demand matching in resource constrained electricity systems. Energy Convers Manage 2003;44:411–37.
[20] Mogulkoc H, Coit D, Felder F. Electric power system generation expansion plans considering the impact of smart grid technologies. Electr Power Energy Syst 2012;42:229–39.
[21] Talukdar SN, Wu FF. Computed aided dispatch for electric power systems. Proc IEEE 1981;69:1212–31.
[22] Hobbs BF. Optimization methods for electric utility resource planning. Eur J Oper Res 1995;83(1):1–20.
[23] Stiphout AV, Poncelet K, Vost KD, Deconinck G. The impact of operating reserves in generation expansion planning with high shares of renewable energy sources. In: IAEE European energy conference, sustainable energy policy and strategies for Europe; 2014. p. 1–15.
[24] Welsch M, Deane P, Howells M, Gallachoir BO, Rogan F, Bazillian M, et al. Incorporating flexibility requirements into long-term energy system models – a case study on high levels of renewable electricity penetration in Ireland. Appl Energy 2014.
[25] Balachandra P. Iimplications of private sector participation in power generation – a case study from India. Energy Pol 2006;34:2466–79.
[26] Cocharn J, Miller M, Zinaman O, Milligan M, Arent D, Palmintier B. Flexibility in 21st century. In: 21st century power partnerships; 2014.
[27] Henderson C. Increasing the flexibility of coal-fired power plants. London: International Energy Agency; 2014.
[28] G. O. I. MNRE. Ministry of new and renewable energy; 30 3 2015. [Online]. Available: http://mnre.gov.in/file-manager/UserFiles/Tentative-State-wise-break-up-of-Renewable-Power-by-2022.pdf.
[29] Becker S, Rodriguez RA, Andresen GB, Greiner MOW, Schramm S. What can transmission do for a fully renewable Europe? In: Proceedings of the 8th SDEWES conference, Dubrovnik; Sep 2013.
[30] Abdullah MA, Agalgaonkar AP, Muttaqi KM. Quantification of emission reduction from electricity network with the integration of renewable resources. In: IEEE power and energy society general meeting; 2011. p. 1–7.
[31] Koltsaklis NE, Georgiadis MC. A mutli-period, multi-regional generation expansion planning model incorporating unit commitment constraints. Appl Energy 2015;158:310–31.
[32] Pereira S, Ferreira P, Vaz A. Generation expansion planning with high share of renewables of variable output. Appl Energy 2017;190:1275–88.
[33] Rajesh K, Kannan S, Thangaraj C. Least cost generation expansion planning with wind power plant incorporating emission using differential evolution algorithm. Int J Electr Power Energy Syst 2016;80:275–86.
[34] Valinejad J, Barforoushi T. Generation expansion planning in electricity markets: a novel framework based on dynamic stochastic MPEC. Int J Electr Power Energy Syst 2015;70:108–17.
[35] Deane JP, Chiodi A, Gargiulo M, Gallachoir OB. Soft-linking of a power systems model to an energy systems model. Energy 2012;72:303–12.
[36] Flores-Quiroz A, Palma-Behnke R, Zakeri G, Moreno R. A column generation approach for solving generation expansion planning problems with high renewable energy penetration. Electr Power Syst Res 2016;136:232–41.

[37] Koltsaklis N, Dagoumas A, Georgiadis M, Papaioannou G, Dikaiakos C. A mid-term, market-based power systems planning model. Appl Energy 2016;179:17–35.
[38] Ministry P. Ministry of power. [Online]. Available: https://powermin.nic.in/en/content/overview [accessed Aug 2018].
[39] NLDC. National Load Dispatch Centre, New Delhi; 2013.
[40] EPS. 18th electricity power survey. Central Electricity Authority, Govt. of India, Delhi; 2013.
[41] Balachandra P, Chandru V. Modelling electricity demand with representative load curves. Energy 1999;24(3):219–30.
[42] Sharma T. Benchmarking and modelling sustainability transition of national electricity system: a case study of India. Bangalore: Indian Institute of Science; 2016.
[43] NEP, National Electricity Plan. Central Electricity Authority, Government of India, Delhi; 2012.
[44] MOSPI. Energy statistics. New Delhi: Ministry of statistics and Programme Implementation, Government of India; 2016.
[45] CEA. Load generation balance report. Delhi: Central Electricity Authority, Government of India; 2014.
[46] MNRE. Ministry of new and renewable energy, Government of India; 30 3 2015. [Online]. Available: http://mnre.gov.in/file-manager/UserFiles/Tentative-State-wise-break-up-of-Renewable-Power-by-2022.pdf.
[47] Chikkatur AP, Sagar AD. Cleaner power in India: towards a clean coal technology roadmap. In: Discussion paper, Belfer Center for Science and International Affairs, Cambridge; 2007.
[48] ESMAP. Model for electricity technology assessment. Energy sector management assistance program. World Bank; 2012.
[49] DEA. Technology data for energy plants. Danish Energy Agency; 2014.
[50] Singh AK, Parida SK. Evaluation of current status and future directions of wind energy in India. Clean Technol Environ Plicy 2012:1–13.
[51] Mongia N, Balachandra P. Energy counting tool for use in costing MDG-based energy needs. Regional energy program for poverty reduction. Bangkok: UNDP; 2009.
[52] CERC. Petition No. SM/004/2015(Suo-Motu). New Delhi: Central Electricity Regulatory Authority; 2015.
[53] CEA. CO2 baseline database. Central Electricity Authority, Govt. of India 2014.
[54] CEA. National electricity plan. Delhi: Central Electricity Authority, Government of India; 2012.
[55] Hernandez L, Baladron C, Aguiar JM, Carro B, Esguevillas AS. Classification and clustering of electricity demand patterns in Industrial parks. Energies 2012;5:5215–28.
[56] Chicco G. Overview and performance assessment of the clustering methods for electrical load patter grouping. Energy 2012;42(1):68–80.
[57] Panapakidis IP, Papadopoulos TA, Christoforidis GC, Papagiannis GK. Pattern recognition algorithms for electricity load curve analysis of buildings. Energy Build 2014;73:137–45.
[58] Tsekouras GJ, Hatziargyriou ND, Dialynas EN. Two-stage pattern recognition of load curves for classification of electricity customers. IEEE Trans Power Syst 2007;22(3):1120–8.
[59] Bobmann T, Staffell I. The shape of future electricity demand: exploring load curves in 2050s Germany and Britain. Energy 2015;90(2):1317–33.
[60] Marton CH, Elkamel A, Duever TA. An order-specific clustering algorithm for the determination of representative demand curves. Comput Chem Eng 2007;32:1373–80.
[61] G. O. I. Ministry of statistics and programme implementation. Energy statistics. New Delhi; 2015.
[62] Boccard N. Capacity factor of wind power: realized values vs estimates; October 2008. [Online]. Available: http://docs.wind-watch.org/Boccard-Capacity-Factor-Of-Wind.pdf [accessed 16 July 2015].
[63] CERC. Performance of solar power plants in India; Feb 2011. [Online]. Available: http://www.cercind.gov.in/2011/Whats-New/PERFORMANCE%20OF%20SOLAR%20POWER%20PLANTS.pdf [accessed 16 July 2015].
[64] V.R.V. Power plants efficiency – capacity utilization factor; April 2015. [Online]. Available: https://www.linkedin.com/pulse/power-plants-efficiency-capacity-utilization-factor-v-r-v [accessed 16 July 2015].
[65] E. Statistics. Energy statistics. New Delhi: Ministry of Statistics and Programme Implementation, Government of India; 2014.
[66] MOSPI. Statistical year book. New Delhi: Ministry of Statistics and Program Implementation, Government of India; 2015.
[67] A. NITI. Niti Ayog; 2015. [Online]. Available: http://niti.gov.in/content/india_energy.php [accessed 16 Jul 2015].